User's Learning Capability Aware E-Content Recommendation System For Enhanced Learning Experience

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Abstract: E-learning is inevitable during these pandemic days and most of the learners find it comfortable to learn online. However, the main challenge is to locate the appropriate data in line with the learner's requirement. Considering the necessity of this issue, this article presents an e-content recommendation system that considers the user's learning capability. This work categorizes the documents into three categories such as basic, intermediate and advanced levels. Based on the users' learning capability, corresponding documents are recommended and this idea enhances the overall learning experience. This work is based on three phases such as data pre-processing, feature extraction and classification. The collected documents are pre-processed for preparing the documents suitable for further processes. Features such as Parts-OF-Speech (POS) tagging, Term Frequency - Inverse Document Frequency (TF-IDF) and semantic similarity based on WordNet are extracted and the multiclass Support Vector Machine (SVM) is employed for distinguishing between the classes. The performance of the work is tested and the results prove the efficacy of the work with 98% accuracy rates, in contrast to the comparative techniques.
Keywords: E-learning, Recommendation System, Learning Experience, Classification, Support Vector Machine.

1. Introduction

E-learning supports teaching and learning using computer and internet. It is a technology-enabled learning process that channels the geographical gap between the learner and, teacher and, provides opportunity for anytime learning. E-learning has grown exponentially in recent years because of the advancement in e-learning technologies and E-learning web sites. Working professionals and, entrepreneurs considered e-learning as a lifetime learning opportunity and, leverage its potential. E-learning removes the barriers to learning and make learning possible from anywhere and at any time with the choice and flexibility of learner.

Teaching and learning no longer bound to the class rooms alone and the e-leaner can learn using their computer, tablet or smart phones from anywhere. Learners will be freed from the barriers of time space and, pace of learning [1]. As the e-learning become widely popular, the e-learning website availability as well the e-learning technologies increased exponentially. Knowledge transfer to certain people would never have been possible without e-learning. Currently multiple e-learning websites are available in every domain from medicine to engineering and, from science to social science and, it's easy for learners to find multiple e-learning web sites for their domain and, thus e-learning provides the learner, the opportunity for lifelong learning.

E-learning can transform an individual with potential learning experiences and, can revolutionize the knowledge transfer process. However, the missing element in all e-learning technologies is the human touch. It reduces the opportunity for interaction and, disrupts the correct learning path. Therefore, the results and learning effectiveness cannot be guaranteed in e-learning.

In order to deal with this issue, several research solutions are proposed in the literature for data analysis and recommendation systems. Considering the merits of e-learning, this article proposes an e-content recommendation system with respect to the learning ability of the user. The learning ability of the user is differentiated into three levels such as basic, intermediate and advanced. This work is sub-divided into four significant phases such as data collection, pre-processing, feature extraction and recommendation based on user's ability. The work highlights are listed below.

- Reader's learning ability is considered for recommending the e-content, which improves the learning experience.
- Real-time data is employed for evaluating the performance of the work.
- The performance of the work is quite satisfactory in terms of precision, recall, F-measure and recommendation time.

2. Related Works

Most investigations on the association between usage patterns and learning styles or academic emotions aimed to identify and construct a particular learning method pattern to improve digital learning and user performance. In [1], the authors described a model with an ACG and an AATG (adaptive affective tactic generator). Questionnaires, self-report, and automatic approaches were utilized to identify student learning styles. Gestures, facial expressions, heart rate, and blood pressure identified affective states. LS stored, updated, and identified information.

The work presented in [2] employed an automatic detection method based on student log files and k-means clustering. Both methods yielded similar results, however questionnaires were less trustworthy and had low precision. Both studies extract learning styles using FSLSM. The work in [3] classified learning style and emotional state using multiple regression. Lesson break, learning, conversation forum, quiz marks, surfing, and navigation time are employed as parameters. Emotions were recognized using non-biological signals.

For more authentic and error-free findings, pupils should be allowed to work at their own pace and preferences, according to [4] and the data were logged. The Bayesian Networks model was created, and data-driven and literature-based prediction methods were compared. Data-driven approach yielded similar results with more authenticity. The model also contained dynamic student modelling technique that regularly updated student model depending on acquired student preferences and behavioural data. This allows real-time assessment of learning styles and affective states.

As per [5], student data is collected and transferred to learning models depending on the thresholds of behaviour. Content items, outlines, navigation, examples, and discussion forums generate patterns. The results are compared to a collaborative questionnaire. In [6], the authors worked on preprocessing methods of weblogs utilized in online usage mining through usage data. The data was preprocessed to eliminate noise before being stored. Preprocessing includes data cleaning, session identification, user identification, and path completion. Apriori algorithms discover patterns.

Articles and blogs related to tuning decision trees [7] as per hyper-parameters such as max depth, min samples split, min samples leaf, max features, etc. to optimize results and avoid over-fitting; understanding AUROC (Area Under the Receiver Operating Characteristics) for performance measurement like overfitting/ underfitting [8] as per its value range between 0 and 1; why normality i.e.

In [11], the authors proposed an automatic student modeling approach that determines learning types. Various approaches to record user learning behavior have been examined. Sow of the ways include verbal, non-verbal, invasive and non-intrusive to capture the emotions of the consumers while they undergo the course on any e-learning website. As per investigations of the authors [12], a conclusion that the emotions related with the learning process vary on a large scale, anxiety being the most prevalent one was derived. Boredom, rage, relief, pride, and happiness were also caught. Their investigation lacked a specific conclusion on emotion reasons.

The authors of [14] used Moodle to collect data and constructed a Bayesian Network-based DDAM model. Using conditional probability, learning styles were determined. Facial emotion identification utilizing live user photos is another method for emotion detection [15]. CNN used average weight to recognize face expressions. This method is useful for continuous real-time image capture. This approach can also capture photos at intervals with the URL and timestamp.

In [16], the authors used artificial neural networks and web usage mining to recognize FSLSM learning styles. Their study featured two prominent aspects: an automated approach for acquiring information on learning preferences and a system that used recent usage history to recognize dimensions. According to [17], authors extracted facial traits by face detection and classified them into 6 emotions: happy, fear, disgust, melancholy, neutral, and rage. For better data classification, Gabor filter, HOG, and DWT were used. HOG performed best, followed by SVM with 85% precision.

In a research on emotion model identification in e-learning [18], situational interaction questions were employed for intuitive learner response. Using an emotion map, each teaching stage's learning process was traced. This emotion map analyzes positive learning areas. Biometric equipment like accelerometers and eye-trackers were used to assess learning styles [19]. These devices can predict global-sequential and visual-verbal learning styles, they found.

In [20], the server-side user logs were kept to analyze user interest. This gave browsing-based recommendations. Personalized ELearning was provided by web usage and content mining. Huong's study revealed difficulties, present practices, and potential in the area of integrating learning styles in e-learning systems. FSLSM is the most common e-learning model, he said. Many classification studies used Bayesian and Neural Networks.

Motivated by these existing works, this paper presents an e-content recommendation system concerning the learning ability of the user, which improves the learning experience. The presented recommendation system is based on an Extreme Learning Machine (ELM) classification.

3. Proposed E-Content Recommendation System Based On Elm Classifier

The main goal of this work is to enhance user's learning experience by recommending appropriate learning content. The recommendation is made by considering the learning ability of the user, which is categorised into basic, intermediate and advanced concepts. The entire work is based on significant phases such as data collection, pre-processing, feature extraction and e-content recommendation. The overall flow of the work is depicted in figure 1.

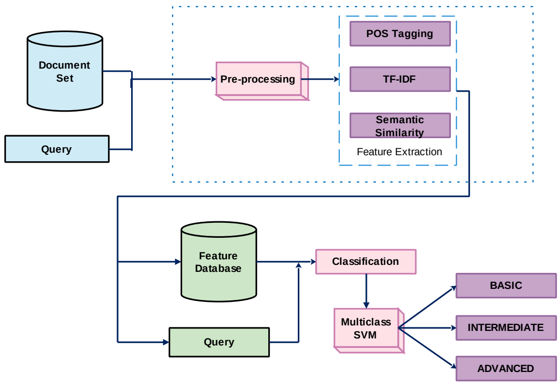

Fig 1: Overall flow of the proposed e-content recommendation system

3.1 Data Collection

This work collects data from several e-learning websites such as W3 schools, guru99, geeksforgeeks and tutorialspoint. Scrappy.spider is utilized to scrap the web pages and the textual files are obtained by 'BeautifulSoup parser API'. These files are stored in local database under separate folder. Hence, the datasets are formed and the text files are manually differentiated into three categories such as 'basic, intermediate and advanced'. This kind of categorization is necessary for testing the performance of the proposed work with respect to classification accuracy.

3.2 Data Pre-processing

The process of pre-processing removes needless information in the textual data, which includes punctuations, quotations and so on. Additionally, meaningless words such as articles, prepositions, pronouns are removed, as the context remains unaffected in spite of its removal. This kind of removal helps in reducing the processing time, while attaining better accuracy rates. As soon as the process of data pre-processing is over, important features are extracted from the documents.

3.3 Features Extraction

This work extracts features by employing Parts of Speech (POS) tagging and Term Frequency - Inverse Document Frequency (TF-IDF) and semantic similarity.

3.3.1 POS Tagging

When the pre-processed documents are passed, the POS tagging process extracts verbs. This procedure extracts verbs, nouns and other POS in the textual data. A feature vector with linear prediction function including weights is employed for prediction.

$$TW = 1\ if\ \sum_{i=1}^{n} w_i * x_i \geq C \quad (1)$$

$$= 0\ if\ \sum_{i=1}^{n} w_i * x_i < C \quad (2) \quad (2)$$

This equation can be re-written as follows.

$$TW = 1\ if\ \sum_{i=1}^{n} w_i * x_i - C \geq 0 \quad (3)$$

$$= 0\ if\ \sum_{i=1}^{n} w_i * x_i - C < 0 \quad (4)$$

In the above equations, TW is the sum of weights, w_i and x_i are the weights and conditions respectively. C is the constant value. Hence, all the verbs and nouns are extracted and the unique words along with their frequencies are extracted.

3.3.2 TF-IDF

The representation of the text documents is done in such a way that the documents themselves are represented as vectors. If there is a significant degree of connection between two documents, then those documents are said to be comparable to one another. Every one of the papers is structured as a vector in the matrix that is the vector space. The term weights of all documents are computed by

$$doc_i = wt_{1i}, wt_{2i}, .. wt_{hi} \quad (5)$$

Where doc_i is the referred document, wt_{1i} is the first term's weight in the i^{th} document and the weight of the h^{th} term in the i^{th} document is represented by wt_{hi}.

$$Vdoc_i = \{wt_{1,i}, wt_{2,i}, .. wt_{h,i}\} \quad (6)$$

The vector space model of the documents is represented by eqn.6. The term weights of the documents are denoted by $wt_{1,i}, wt_{2,i}$, which are computed by

$$wt_{h,i} = tf_h * IDF \quad (7)$$

$$\text{IDF} = \log\left(\frac{Doc}{docf_h}\right) \quad (8)$$

tf_h is the h's repetition frequency in the i^{th} document, $docf_h$ is the total number of documents with the term h, total count of documents in the dataset is indicated by Doc. The significance of each term determines how much weight should be given to the entire document. Nevertheless, the focus of the equations 5 through 8 shown above is solely on the occurrence frequency of the terms. The formulation of the vector space model takes into account the semantic connotations of the term and is described below.

3.3.3 Semantic Similarity

The inclusion of wordnet [21-25] performs the computation of the semantic similarity between phrases. Wordnet is a lexical database that gathers together groups of words that are referred to as synsets. The semantic correlation between the phrases is used to perform the calculation that determines the semantic link between the terms. In wordnet, each word is analyzed to determine the semantic relationship it shares with the other words in the database.

The semantic connection between the two phrases wd_1 and wd_2 is denoted by the notation $\alpha_{h1,h2}$. If wd2 is included in the synset of wd_1, then $\alpha_{h1,h2}$ will have a value of 1, and if it is not, then $\alpha_{h1,h2}$ will have a value of 0 and will be represented in eqn. (9).

$$\begin{cases} wd_2 \in wd_1 & \alpha_{h1,h2} = 1 \\ wd_2 \notin wd_1 & \alpha_{h1,h2} = 0 \end{cases} \quad (9)$$

The weight wd_{ij1} of term t_{i1} in document doc_x is given by (10).

$$wd_{ij1} = wd_{ij1} + \sum_{\substack{h2=1 \\ h2 \neq h1}}^{i} \alpha_{h1,h2}\ wd_{ij2} \quad (10)$$

The semantic connection between every possible pair of phrases can then be determined using this method. The next step is to compute the degree of similarity between the two sets. This work, which is presented in, makes use of the cosine similarity that exists between the documents, as given in equations 11 and 12.

$$Sim(Doc_a, Doc_b) = cosine(Doc_a, Doc_b) \quad (11)$$

$$cosine(Doc_a, Doc_b) = \frac{\sum_{i=1}^{n} wd_{ij1} wd_{ij2}}{\sqrt{\sum_{i=1}^{n} wd_{ij1}^2 . wd_{ij2}^2}}, a \quad (12)$$

The semantic similarity between the terms and the documents can then be determined thanks to this process. The next stage, which is the classification procedure, comes after this step.

3.4 SVM Classification

This work employs multiclass SVM for distinguishing between the learning ability of the user such as basic, intermediate and advanced. It is better to employ multiclass SVM rather than binary SVM. This is because, a binary SVM can classify between two categories only. In this case, a binary SVM can differentiate between two classes alone.

SVM can be implemented in two distinct ways to tackle problems involving many classes. The first method employs several binary SVM classifiers, each trained to handle a single class from a set of classes. In the second method, multiple classifiers are applied to each pair of classes, and pixels are assigned to the class with the highest computed score. This technique requires the selection of n(n-1)/2 classifiers, followed by the max-vote strategy [23]. This work conducts multiclass classification by proposing the idea of simultaneously handling all classes by resolving a single objective function, as shown below. In general, a hyperplane divides two distinct classes, and it can be represented as follows.

$$w.x_i + b \geq +1;\ y_i = +1 \qquad (13)$$

$$w.x_i + b \leq -1;\ y_i = -1 \qquad (14)$$

where x_i is a point, b is the bias, w appears normal to the hyperplane. However, this case is not possible, as the data points cannot be separated in a linear fashion. This issue is overcome by slack variables $\{\omega_i\}_{i=1}^{r}$. The equation can be rewritten with the slack variables as

$$y(w.x_i) + b > 1 - \omega_i \qquad (15)$$

This case is observed whenever ω_i is large, thus a penalty term $C\sum_{i=1}^{r}\omega_i$ is added. C is the constant, which is responsible for managing the magnitude of the penalty being linked with the training items that are on the opposite side of the decision borderline. When the value of C is smaller, more support vectors are defined. On the other hand, when the value of C is greater, the training samples are overfitted. When the penalty term is included, the equation becomes

$$min\left(\frac{||w||^2}{2} + C\sum_{i=1}^{r}\omega_i\right) \qquad (16)$$

In our case, $n(n-1)/2$ classifiers are employed over every single pair of classes. For instance, when a data item is decided to be placed in class A, then the vote for class A is incremented by 1. By thus way, the decision outcomes are added and the class with the greatest decision value is chosen. This method involves a single optimization issue to be solved. When the problem has n different classes, then the single optimization problem can be written as

$$\min_{w,b,\omega} \frac{1}{2}\sum_{y=1}^{n} w_y^p\, w_y + C\sum_{i=1}^{l}\sum_{y\neq s_i}\omega_{i,y} \qquad (17)$$

The constraints followed by eqn.17 are given below.

$$w_{s_i}^p\rho(x_i) + b_{s_i} \geq w_y^p\rho(x_i) + b_y + 2 - \omega_{i,y};\ \omega_{i,y} \geq 0$$

(18)

where $i = 1,2, \dots l$ are training samples and $y \in \{1,2, \dots n\}$. The final decision is obtained by the below given equation.

$$dec_{fn} = \max_{y=1,2,..n}(w_y^p\rho(x_i) + b_y) \qquad (19)$$

This approach is optimal and time conserving, as the multiclass problem is confined to a single optimization problem. Additionally, this approach needs minimal support vectors when compared to the usage of multiple binary SVMs. Thus, the multiclass SVM can serve its purpose, irrespective of the class count. The proposed work differentiates between the basic, intermediate and advanced levels effectively.

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4. Results And Discussion

In this section, the performance of the proposed algorithm is verified by comparative analysis made by varying feature extraction techniques. This work recommends documents concerning the learning ability of users with respect to the categories of basic, intermediate and advanced. In the existing literature, recommendation systems for learners with respect to learning ability is quite scarce and hence, the performance of the proposed work is analysed by varying the feature extraction approaches such as POS tagging, TF-IDF and semantic similarity techniques. The datasets which are exploited for the experimentation process are W3 schools, Guru99, GeeksforGeeks and tutorialspoint. The proposed work is implemented in Matlab 2021A on a stand-alone computer with 8 GB RAM.

4.1 Performance metrics

Precision, recall, f-measure, and accuracy are the performance metrics that are utilized in order to evaluate the effectiveness of the proposed algorithm. When all of the documents that belong to a class are compared to their actual class label, precision and recall statistics may be computed for the cluster as a whole.

Precision: Precision is determined by comparing the number of documents that fall under the class i but were incorrectly classified by the proposed work with label j to the total number of documents that have the label j. This is computed by (20).

$$Prec(i,j) = \frac{doc_{ij}}{doc_j} \tag{20}$$

where doc_{ij} is the total number of documents that should be categorized as belonging to class i, but were instead assigned to class j, due to an error in the classification process. doc_j is the number of documents that may be categorized as belonging to the label j. The levels of precision achieved by the algorithms under consideration for the various datasets are illustrated in figure 2.

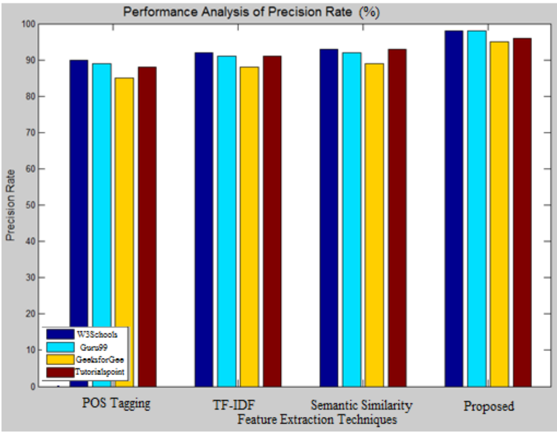

Fig 2: Comparative analysis of precision rate

Based on the findings of the experiments, it is clear that the suggested work has a precision rate that is significantly higher than that of other feature extraction strategies. When combined, the three distinct methods of feature extraction produce superior results to those obtained by their individual application. The proposed work has an accuracy rate that falls somewhere between 95.82 and 98.18 percent.

Recall: Recall is the number of documents that, in reality, belong in the i category, but for whatever reason, they have been erroneously filed under the j category. This can be determined by

$$Rec(i,j) = \frac{doc_{ij}}{doc_i} \tag{21}$$

where the total number of documents that should be categorized under i but have been incorrectly categorized as j by the proposed work is denoted by the variable doc_{ij}. doc_i is a count of the number of documents that are categorized with the i label. The comparison study of the recall rates is carried out by taking into consideration four different datasets, and the findings are shown in figure 3.

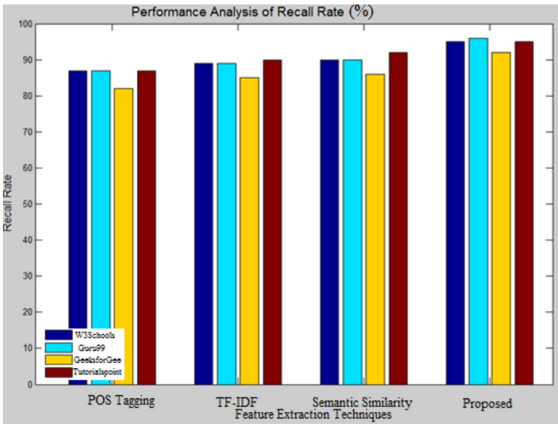

Fig 3: Comparative analysis of recall rate

It has been demonstrated that the proposed method demonstrates an excellent recall rate by conducting an analysis of the experimental results of recall rate with regard to various datasets. The proposed work has a recall rate that falls somewhere in the range of 92.19 and 97.36%.

***F-measure**:* The final categorization result of the documents is referred to as the F measure, and it is determined by taking into account both their precision and their recall (22).

$$Fm = \sum_i \frac{doc_i}{doc\_count} \max_j (F_m(i,j)) \qquad (22)$$

Where $F_m(i,j)$ is the f-measure and is calculated by (23)

$$F_m(i,j) = \frac{2 \times prec(i,j) \times rec(i,j)}{prec(i,j) + rec(i,j)} \qquad (23)$$

There is a one-to-one relationship between the value of the F-measure and the accuracy of the classification result. It is clear from the experimental analysis that the suggested work has a higher F measure than the techniques that were used for comparison; this is illustrated in figure 4.

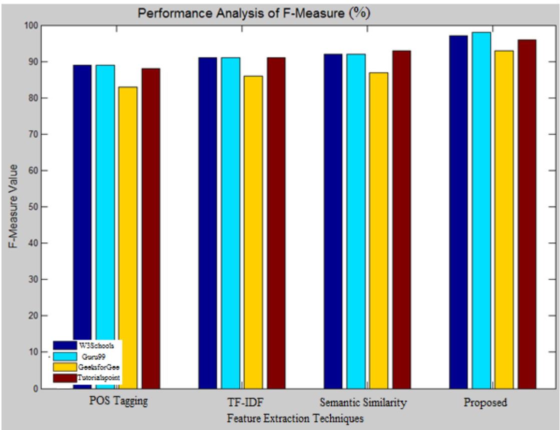

Fig 4: Comparative analysis of recall rate

When the results were analyzed, our proposed method came out on top, outperforming all of the other algorithms that were tested with greater F-measure rates. The value of the F-measure has a direct and proportional relationship to the quality of the outcomes. The F-measure rate of the algorithm falls in the range between 92.97 and 98.17%. As a result, it has been determined that the suggested method has a classification quality that is satisfactory.

Accuracy: The efficiency with which the algorithm classifies different types of documents is directly proportional to the rate of accuracy achieved. The accuracy rate achieved by the algorithm that has been proposed is significantly higher than that achieved by other techniques.

$$accuracy = \frac{c.a.d + c.r.d}{clustered\ documents} \qquad (24)$$

where c.a.d stands for the document that has been correctly accepted by the classification algorithm and c.r.d stands for the document that has been appropriately rejected. The suggested algorithm's accuracy was evaluated using a variety of datasets, and the findings are depicted in figure 5.

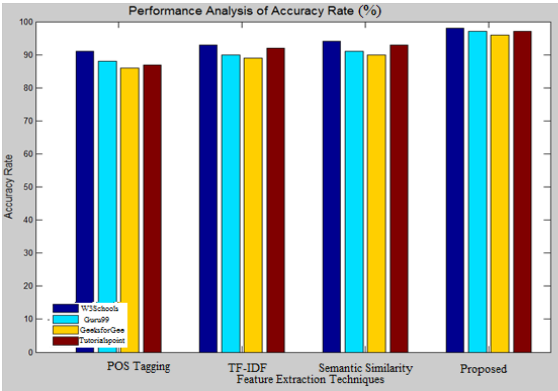

Fig 5: Comparative analysis of accuracy

Differentiating between the various types of documents is the primary goal of the algorithm that has been proposed, as this will lead to an increase in the accuracy rate of classification. The accuracy rates that are being demonstrated by the suggested algorithm fall in the range of 96 to 98 percentages. Our suggested algorithm is able to accomplish this, and the level of accuracy it achieves is adequate.

Misclassification Rate*:* The percentage of documents that were incorrectly classified is known as the misclassification rate, and it is computed by dividing the total number of classified documents by the number of documents that were incorrectly classified (25).

$$mr = 100 - accuracy \qquad (25)$$

The percentage of incorrect classifications can be expressed as a misclassification rate by subtracting the accuracy rate from 100. It is asserted that the classification algorithm is effective, with a low rate of incorrect classifications. The proposed algorithm is put through a series of tests to determine its rate of misclassification, and the results are depicted in figure 6.

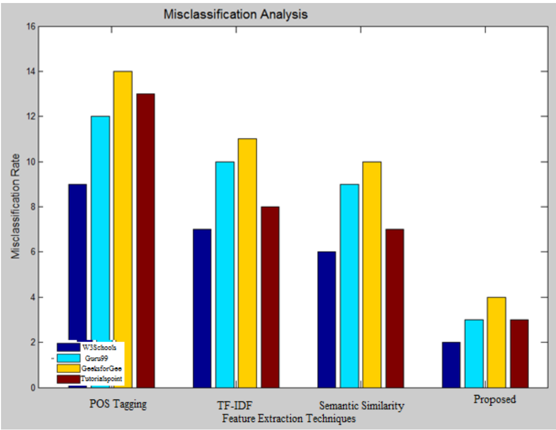

Fig 5: Comparative analysis of misclassification rate

When compared with all of the other techniques, the proposed algorithm has the lowest rate of incorrect classification. The fact that the proposed recommendation system has a lower rate of incorrect classification demonstrates that its performance is superior. Because the proposed algorithm displays a misclassification rate of between 2 and 4, the results are more accurate as a direct consequence of this. As a result, the performance of the work is assessed, and the results that this work produces are superior.

5. Conclusions

This paper presents an e-content recommendation system for users by considering the learning ability. The documents are categorised under three classes such as basic, intermediate and advanced levels and the users are recommended with appropriate content. This goal is attained by enforcing three major steps, where the initial step pre-processes the documents, while the second phase is concerned with the extraction of features such as POS tagging, TF-IDF and semantic similarity. Finally, SVM classifier is employed for differentiating the document under three classes and the user is suggested with the content of the respective class. This idea enhances the learning experience and the performance of the work is justified in terms of standard performance measures. In future, this work can be enhanced by considering the emotions of learners for e-content recommendation.

References

[1] Farman Ali Khan, Sabine Graf, Edgar R. Weippl, A Min Tjoa., “Implementation of Affective States and Learning Styles Tactics in Web-based Learning Management Systems, Institute of Software Technology and Interactive Systems”, Vienna University of Technology, Austria, DOI 10.1109/ICALT.2010.213, IEEE 2010.

[2] Ouafae El Aissaoui, Yasser El Madani El Alami, Lahcen Oughdir, Youssouf El.: “Integrating web usage mining for an automatic learner profile detection: A learning styles-based approach”, IEEE-2018.

[3] Sandanayake T.C, Madurapperuma A.P, and Dias D: “Affective E-Learning Model for Recognising Learner Emotions”, International Journal of Information and Education Technology, Vol. 1, No. 4, October 2011.

[4] Khan F.A, Akbar A, Muhammad Altaf, Shujaat Ali Khan, Ayaz Ahmed, “Automatic Student Modelling for Detection of Learning Styles and Affective States in Web based Learning Management Systems”, DOI10.1109/ ACCESS.2019.2937178, IEEE Access.

[5] Sabine Graf; Kinshuk; Tzu-Chien Liu, “Identifying Learning Styles in Learning Management Systems by Using Indications from Students' Behaviour”, 2008 Eighth IEEE International Conference on Advanced Learning Technologies.

[6] V. Chitraa, Dr. Davamani A. S: “A Survey on Pre-processing Methods for Web Usage Data”: (IJCSIS) International Journal of Computer Science and Information Security, Vol. 7, No. 3, 2010.

[7] How to tune a decision tree. [Online]. Available: https://towardsdatascience.com/how-to-tune-a-decisiontreef03721801680

[8] Understanding AUC-ROC Curve. [Online]. Available: https://towardsdatascience.com/understanding-auc-roccurve68b2303cc9c5

[9] A Gentle Introduction to Normality Tests in Python. [Online]. Available: https://machinelearningmastery.com/a-gentleintroductionto- normality-tests- in-python/

[10] Feature Selection with sklearn and Pandas. [Online]. Available: https://towardsdatascience.com/feature-selection-withpandase3690ad8504b.

[11] Farman Ali Khan, Sabine Graf, Edgar R. Weippl, A Min Tjoa.: “Identifying and Incorporating Affective States and Learning Styles in Web- based Learning Management Systems”, Interaction Design and Architecture(s) Journal - IxD&A, N. 9-10, 2010, pp. 85-103, 2010.

[12] Reinhard Pekrun, Thomas Goetz, and Wolfram Titz: “Academic Emotions in Students’ Self-Regulated Learning and Achievement”: A Program of Qualitative and Quantitative Research, Educational Psychologist 37(2002)

[13] Felder, Richard M. and Silverman L.K: Learning and teaching styles in engineering education 1998

[14] Soni Sweta and Kanhaiya Lal; “Web Usages Mining in Automatic Detection of Learning Style in Personalized e-Learning System”; Springer International Publishing Switzerland 2015

[15] Keng-Cheng Liu, Chen-Chien Hsu, Wei-Yen Wang, Hsin-Han Chiang; “Real-Time Facial Expression Recognition Based on CNN”; 2019 International Conference on System Science and Engineering (ICSSE).

[16] Sucheta Kolekar, Sriram G. Sanjeevi, D. S. Bormane; “Learning style recognition using Artificial Neural Network for adaptive user interface in e- learning”; Computational Intelligence and Computing Research (ICCIC), 2010 IEEE International Conference.

[17] Jain Charvi, Sawant Kshitij, Mohammed Rehman, Rajesh Kumar; Emotion Detection and Characterization using Facial Features; 3 rd international conference and workshops on recent advances and innovations in engineering, 2018.

[18] Guey Shya Chen, Min-Feng Lee; “Detecting Emotion Model in elearning System”; Proceedings of 2012 International Conference on Machine Learning and Cybernetics, Xian.

[19] Tracey J Mehigan, Ian Pitt; “Detecting Learning Style through Biometric Technology for Mobile GBL”; Internation Journal of Game-Based Learning, April-June, 2012.

[20] Manasi Chakurkar, Prof.Deepa Adiga: “A Web Mining Approach for Personalized E-Learning System”, (IJACSA) International Journal of Advanced Computer Science and Applications, Vol. 5, No. 3, 2014.

[21] D. Hindle, Noun classification from predicate-argument structures, Proc. of the Annual meeting of the association for computational linguistics, pp. 268-275, 1990.

[22] S. Caraballo, Automatic construction of a hypernymbased noun hierarch from text, Proc. of the Annual meeting of the association for computational linguistics, pp. 120-126, 1999.

[23] P. Velardi, R. Fabriani, and M. Missikoff, Using text processing techniques to automatically enrich a domain ontology, Proc. of the international conference on Formal ontology in information systems, pp. 270-284, 2001.

[24] P. Cimiano, A. Hotho, and S. Staab, Learning concept hierarchies from text corpora using formal concept analysis, Journal of Artificial Intelligence Research, 24 (2005), pp. 305-339.

[25] C. Fellbaum, WordNet: an electronic lexical database, MIT Press., 1998.